Noise Removal from Chrominance Components of a Television Signal

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Abstract:
A solution to the problem of removing **noise** from the **chrominance** compon color television signal is described. The inherent trade-off between **noise** rem signal blurring is balanced adaptively using the **luminance** signal as a contro changing the characteristics of the **chrominance** filters. This adaptation is ef because: (1) in real pictures, most sharp changes of color are accompanied b changes in **luminance** and, (2) sharp changes of **luminance** have a pronour masking effect on the **chrominance noise**. Computer simulations show that amount of **noise** could be removed from the **chrominance** signals with no a visible blurring. A simple filter, whose performance is close to the optimum, is and a comparison with nonadaptive filters is made.

Index Terms:
Digital image processing Image processing, digital TV receiver signal processing

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up to $W = f_s/2F$. In the Markov model these correspond to frequencies of $1/2$ and $1/2F$ because of normalizing f_s to unity.

The noise rejection G is therefore given by

$$G = \frac{\int_0^{1/2} S_{QQ}(e^{j2\pi f})df}{\int_0^{\frac{1}{2F}} S_{QQ}(e^{j2\pi f})df}. \tag{8}$$

Using (5) and a standard integration result [5]

$$\int \frac{dz}{a + b\cos Z} = \frac{2}{(a^2 - b^2)^{1/2}} \arctan \frac{(a-b)\tan\frac{Z}{2}}{(a^2-b^2)^{1/2}} \quad \text{if } (a^2 > b^2) \tag{9}$$

we obtain the following expression for G in terms of the autocorrelation $(-1 < C < 1)$ and the oversampling F:

$$G = \frac{\pi/2}{\arctan\left|\frac{1+C}{1-C}\tan\frac{\pi}{2F}\right|}. \tag{10}$$

DM inputs are often highly over sampled ($F \gg 1$). The following asymptotic expression G_∞ is therefore of interest:

$$G_\infty = \frac{1-C}{1+C} \cdot F \qquad \text{if } F \gg \frac{1+C}{1-C} \cdot \frac{\pi}{2}. \tag{11}$$

Clearly, (11) results from applying the approximation ($\arctan X = X$ if $X \ll 1$) to (10).

Two values of the autocorrelation C are worth special mention:

$$G_\infty = F \qquad \text{if } C = 0 \tag{12}$$

$$G_\infty = 2F \qquad \text{if } C = -1/3. \tag{13}$$

The case of $C = 0$ corresponds to a flat spectrum in which case the noise-rejection is clearly identical to the oversampling factor F. This situation is often tacitly assumed as an idealized model for "optimally loaded" DM systems (with a well-balanced mix of slope-overload and granular errors). The case of $C = -1/3$ on the other hand typifies a high-pass noise spectrum and the corresponding noise rejection of $2F$ is in fact precisely what has been noted (implicitly in Figure 2 of [2] and explicitly in [3]) in mathematical analyses of DM noise with a no-slope-overload assumption (specifically, with the assumption of so-called 4-sigma loading [2], where sigma refers to the standard deviation of the input slope). One expects the autocorrelation C to decrease from 1 to -1 as the loading (step-size) increases from 0 to ∞; and it is interesting that the classical 4-sigma assumption corresponds to a noise process whose autocorrelation is $-1/3$.

Table I lists values of G for several target values of C and F. Notice, in the case of $C = -1/3$, that $F = 4$ provides a G value (=7.6) that is already fairly close to the asymptotic value $G_\infty = 2F = 8$.

TABLE I
EFFECTS OF C AND F ON NOISE-REJECTION FACTOR G

C	Remarks	$F = 1$	$F = 2$	$F = 4$
1	Extreme Overload	1	1	1
1/3	—	1	1.4	2.3
0	"Optimal" Loading	1	2	4
−1/3	"Four-Sigma" Loading	1	3.4	7.6
−1	Extreme Granularity	∞	∞	∞

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Noise Removal from Chrominance Components of a Color Television Signal

ARUN N. NETRAVALI

Abstract—A solution to the problem of removing noise from the chrominance components of a color television signal is described. The inherent trade-off between noise removal and signal blurring is balanced adaptively using the luminance signal as a control for changing the characteristics of the chrominance filters. This adaptation is effective because; (1) in real pictures, most sharp changes of color are accompanied by sharp changes in luminance and, (2) sharp changes of luminance have a pronounced masking effect on the chrominance noise. Computer simulations show that a large amount of noise could be removed from the chrominance signals with no appreciable visible blurring. A simple filter, whose performance is close to the optimum, is proposed and a comparison with nonadaptive filters is made.

I. INTRODUCTION

Digital image restoration has received considerable attention in the past few years. Availability and use of digital computers has allowed application of numerous sophisticated schemes for restoration. Most of the work, however, has been limited to restoring monochrome grey-tone images[1-4]. Color information and displays being more acceptable, color image restoration is beginning to receive consideration[5].

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In this paper, filters for removing noise from the chrominance components of a color television signal are considered. Noise removal is important in a variety of applications. First, it makes the picture look more pleasing. Second, it is easier to reduce bit rates of filtered images since most of the unnecessary information introduced by noise is removed by filtering. It is assumed, in most of the paper, that the luminance signal is relatively noise free and noise-removing filters are adapted under the control of the luminance signal. This assumption is valid in some digital coding applications where the luminance signal is coded by a good coder and the chrominance is coded more coarsely. The quantizing noise in the chrominance signal can then be removed at the receiver by applying the techniques of this paper. Also in other applications, where the noise is present in the luminance signal, it could be removed by one of the many filtering techniques[1-4] which are relatively complex, and the filtered luminance signal can be used to adapt the filtering of the chrominance signal. Such a strategy passes on most of the filtering complexity to the luminance signal and keeps the chrominance filtering simple.

Use of the luminance signal to control the filtering of the chrominance signal has some advantages. Sharp spatial transitions in the luminance signal provide better noise masking properties than the spatial transitions in the chrominance signal[6]. This has the effect of adapting the chrominance filter characteristics in a visually pleasing way. In real pictures most spatial transitions in chrominance are accompanied by spatial transitions in the luminance and therefore chrominance filter adaptation based on the luminance signal does not blur most of the chrominance edges.

In the next section, the optimization problem for adaptive filters is presented. Although the optimization is rather simple, a different optimization problem has to be solved for every chrominance sample and this makes the noise removal process time consuming and expensive. A simple, suboptimum filter is therefore developed whose performance is close to the optimum. In section III, we give details of computer simulations including comparisons between the performance of adaptive and nonadaptive filters.

II. THE APPROACH

The mathematical approach given in this section follows our earlier work[4] on filtering monochrome images. Let the chrominance components of a color television signal be corrupted by additive independent noise samples, and the corrupted chrominance signals ($Z^{C_1}(x, y)$, $Z^{C_2}(x, y)$) be represented by:

$$Z^k(x, y) = S^k(z, y) + n^k(x, y), \qquad k = C_1, C_2 \tag{1}$$

where $S^k(x, y)$ is the true chrominance signal and $n^k(x, y)$ is the noise. We work on the sampled and digitized version of equation (1) and develop a one-dimensional version of our filter. A two-dimensional version, which was simulated, is straightforward. The noise samples are assumed to be identically distributed, with zero mean and variance σ_k, i.e.,

$$E\,[\,n_i^k n_j^k\,] = \sigma_k{}^2 \delta_{ij}, \qquad k = C_1, C_2 \tag{2}$$

where $E[\cdot]$ is the expectation operator and δ_{ij} is the Kronecker delta function. The two chrominance signals are filtered independently of each other. The input-output characteristic of these filters is represented by

$$\hat{Z}_i^k = \sum_{l=-p}^{l=p} a_l Z_{i-l}{}^k, \qquad k = C_1, C_2 \tag{3}$$

where Z_i^k is the ith noise corrupted chrominance sample, $\hat{Z}_i^k$ is its filtered value, and $\{a_l\}_{l=-p,\cdots,p}$ are the filter weights. The filtered noise has zero mean and variance given by $\sigma_k a^T a$ for $k = C_1, C_2$, where $a = \text{col}\,(a_{-p}, a_{-p+1}, \cdots, a_p)$ and the superscript T denotes the transpose. The visibility of this noise depends on several characteristics of the picture signal and in general varies considerably within a picture. Part of this variation is accounted for by considering its dependence on the luminance spatial detail as measured by the luminance slope $m_i{}^L = |\,S_i{}^L - S_{i-1}{}^L\,|$. The visibility function that we borrow from our earlier work [6] relates the visibility of the noise in the chrominance signal to the slope of the luminance signal. It provides a weighting which when multiplied by the noise power gives the visibility of the noise. It is obtained by subjective tests and, in general, found to decrease with respect to the luminance slope and this decrease is approximately exponential. Visibility function is picture dependent; however, as we will observe later, by using the visibility function of a head and shoulders type of picture on many other pictures, quite good restorations are possible. The visible noise is then given by $f_k(m_i{}^L)\sigma_k a^T a$, where $f_k(\cdot)$ is the visibility function for the kth chrominance signal.

The tendency of the filter to produce visible blur is determined to a large extent by how many dissimilar chrominance samples it averages. Assuming that the spatial transitions in the luminance and the chrominance occur at the same place, we take the following quadratic form as a measure of the blur introduced by the filtering operation:

$$\begin{aligned} \text{Blur}_i &= \sum_{l=-p}^{l=+p} a_l \Phi(S_{i-l}{}^L - S_i{}^L) a_l \\ &\triangleq a^T D a \end{aligned} \tag{4}$$

where $\Phi(\cdot)$ is a positive nondecreasing function. If the ith and the $(i-l)$th luminance samples are much different from each other, then Φ corresponding to weight a_l is high and when the blur is minimized, it decreases a_l and consequently a small contribution from the $(i-l)$th chrominance sample gets added to the filtered chrominance signal.

We are now in a position to state the optimization problem for obtaining the filter characteristics: obtain the filter weights $\{a_l\}_{l=-p,\cdots,p}$ such that they minimize the following quadratic form:

$$\alpha \cdot f(m_i{}^L)\sigma_k a^T a + (1-\alpha) a^T D a \tag{5}$$

where α is a positive constant between 0 and 1, which reflects the amount of relative importance given to noise removal as compared to blurring. In order to keep the average value of the filtered signal the same as that of the unfiltered signal, we minimize (4) under the constraint

$$\sum_{l=-p}^{l=p} a_l = 1. \tag{6}$$

For each value of α the above problem can be easily solved. The answer is given by:

$$a = \lambda[\alpha \cdot f(m_i^L)\sigma_k I + (1-\alpha)D]^{-1}u \tag{7}$$

where λ is a Lagrange multiplier, I is the identity matrix of appropriate size, and u is $(2p+1)$ vector given by

$$u = \text{col}\,(1, 1, \cdots, 1). \tag{8}$$

We note that above 'a' is easy to compute since the quantity in square brackets is a diagonal matrix. The filter is adapted by choosing a suitable value of α. For each picture element, α is taken such that the visible noise, i.e., $\sigma_k f(m_i^L) a^T a$, is constant throughout the picture. In the flat areas of the picture $f(\cdot)$ is large and therefore a large α is used which gives more importance to noise removal. This results in relatively flat filter weights. On the other hand in areas of high spatial detail $f(\cdot)$ is small and a small α gives high weighting to blurring and therefore filter weights are sharply peaked. As a simplification we considered $\Phi(\cdot)$ to be given by:

$$\Phi(x) = 0 \qquad \text{if } |x| \leq T$$
$$= 1 \qquad \text{otherwise.} \tag{9}$$

The optimum filter using the above formulation was simulated. The results are given in the next section.

Although the optimum filter is rather simple, a different optimization problem has to be solved at each picture element to evaluate the filter weights. To reduce the complexity further, we implemented the following simple, but suboptimum, filter. The filter weights $\{a_l\}_{l=-p,\cdots,p}$ were taken to be:

$$a_l = \bar{a}_l \cdot [1 - \Phi(Z_{i-l}^L - Z_i^L)] \tag{10}$$

where $\bar{a}_l$ is a fixed weight which decreases as a function of l and $\Phi(\cdot)$ is defined by equation (9). The weights were then adjusted so that their sum was equal to one. Thus the filter took a weighted average of all the surrounding picture elements which are sufficiently close to the picture element being filtered, as determined by the luminance signal. The fixed weights $\bar{a}_l$ are taken such that their value decreases as l gets larger, i.e., as the element to be used in the filter gets farther away spatially from the element at which filter output is derived. In the next section, we discuss the results of simulations using the above techniques and compare them.

III. COMPUTER SIMULATIONS

Computer simulations were done on a variety of pictures. All the pictures were obtained in digital form by Nyquist sampling and linear 8-bit PCM quantization of the three color (red, green, and blue (R, G, B)) components filtered to 1 MHz. The resulting picture was a $3 \times 256 \times 256$ spatial array. The red, green, and blue signals were matrixed as follows to obtain the luminance and chrominance signals:

$$S^L(x,y) = 0.299R(x,y) + 0.587G(x,y) + 0.114B(x,y)$$

$$S^{C}1(x,y) = \frac{1}{1.14}(R(x,y) - S^L(x,y))\cos 33^0 + \frac{1}{2.03}(B(x,y) - S^L(x,y))\sin 33^0$$

$$S^{C}2(x,y) = \frac{1}{1.14}(R(x,y) - S^L(x,y))\sin 33^0 + \frac{1}{2.03}(B(x,y) - S^L(x,y)\cos 33^0. \tag{11}$$

The $S^C1(x,y)$ and $S^C2(x,y)$ are similar to the (I, Q) chrominance components specified by the NTSC. The noisy pictures were generated by adding pseudo-random digital noise to the chrominance components. Although most of our simulations were done with zero mean, uniformly distributed noise, we also used zero mean, Gaussianly distributed noise and found small differences in all the results. The noisy pictures were generated by adding noise of 10 units (peak) out of 255 to both the chrominance components. These signals were filtered and dematrixed before displaying on the color monitor.

III-1 Optimal Filtering of Chrominance Signals

We first simulated the optimal filters of the previous section. Two-dimensional filters of sizes 3×3, 5×5, and 7×7 were used. No attention was paid to interlace, i.e., all the picture elements used by the filter were not from the same field. These optimal filters used the visibility function given in Figure 4 of Reference (6). Since in most pictures the chrominance signals can be filtered rather severely without noticeable degradation, a large value of α generally was preferable. A 7×7 filter did significantly better than 3×3. However, a 5×5 filter did better than 3×3 and 7×7 from the overall point of view of blurring and noise removal. To evaluate the effects of visibility function, we processed some pictures using $f(\cdot) = 1$ and found that the filtered pictures were of reasonable quality. The noise was not well distributed, i.e., there were many flat areas in the picture where the noise was clearly visible. This could be filtered out by increasing the value of α, but only at the cost of blurring of certain edges in the picture. Thus the inclusion of the visibility function does improve the performance of the filter. The effect of the blurring term (i.e., D matrix) in the performance index (equation (5)) was evaluated by varying threshold T in the definition of $\Phi(\cdot)$ of equation (9). Small values of T did not filter the noise well, and large T resulted in blurred images. Although best threshold varied from picture to picture, a value between 5–10 was found to be an acceptable trade-off.

III-2 Suboptimal Filters

In order to reduce the computations, we simulated the suboptimum filters described in the previous section. Essentially, these suboptimum filters obtained a weighted average of those picture elements in a neighborhood which were found to be within a threshold of the picture element being filtered, as determined by the luminance signal. We took the fixed weights $\bar{a}_l$ (equation (10)) to decrease exponentially, i.e.,

$$\bar{a}_l = e^{-\delta |l|}. \tag{12}$$

We used 0.5, 0.1, 0.0 as values of δ. In general, $\delta = 0.5$, gave poor quality pictures, and $\delta = 0.1$, 0.0 gave comparable pictures. On very busy pictures $\delta = 0.1$ performed better. As in the case of optimum filters, filters with size 5×5 gave

better quality pictures compared to sizes 3 X 3 and 7 X 7. Compared to the optimum filters, the suboptimum filters certainly were inferior. Noise was not equally visible in the picture. Small flat areas with surrounding detail seemed to suffer the most, since there the noise visibility was high, and because of the surrounding detail the filter did not average a large number of picture elements and consequently did not efficiently filter out the noise. Compared to the constant (nonadaptive) filter, the performance of the optimum as well as the suboptimum filter was clearly superior. As would be expected, the constant filter either removed the noise or preserved the resolution, but could not do both.

One of the causes of degradations in adaptive filters is the adaptation based on the luminance signal. Although the degradations were not visible in most pictures, there were certain places in some pictures where the degradation was visible. If the picture had a few luminance edges which were not accompanied by the chrominance edges, then the noise would not be removed from the chrominance signal. However, in most cases, especially with the optimum filters, the unfiltered noise in the chrominance signal was masked by the edges of the luminance signal and consequently the picture quality did not suffer significantly. If, however, the picture had some chrominance edges which were not accompanied by the luminance edges, the noise was removed and the edges were blurred, resulting in a poor picture. As mentioned earlier, this happened only in some pictures and at very few places in these pictures. It could be corrected to some extent by considering both the chrominance edges and the luminance edges in the definition of D. We did not, however, simulate this modification.

We mentioned in the Introduction that in all our simulations chrominance filtering was controlled by a relatively noise-free luminance signal. To evaluate the sensitivity of the suboptimum filters to luminance noise, we added uniformly distributed noise in the luminance and used this noisy luminance signal for controlling the chrominance filters. The filtered picture consisted of luminance filtered by one of our previous techniques[4] and chrominance filtered by the suboptimum techniques of the present paper. A small amount of noise (5 units out of 255) did not affect the picture quality significantly. However, as the noise was increased the filters began to perform poorly. When the luminance noise was uniformly distributed, zero mean and peak 10 units, the picture quality was poor. Some improvement was obtained by raising the threshold used in the definition of $\Phi(\cdot)$. Picture quality was remarkably improved by first filtering the luminance signal by one of our earlier techniques[4] and then using the filtered luminance signal for controlling the chrominance filtering.

All our simulations so far were done using surrounding chrominance samples which were not necessarily from the same field. In real-time applications, this would require a field memory. To avoid the need of a field memory, we took the chrominance samples from the same field for filtering. These filters did not have as good an ability to remove noise as the previous filters. However, they would perform better in sequences of television frames containing motion.

IV. SUMMARY

We have described techniques for adaptively filtering the chrominance components of a color television signal. Specifically, we posed an optimization problem whose solution gave us the weights for a two-dimensional, finite impulse response filter. We then described a suboptimum filter whose performance was close to the optimum filter, but was simple to compute and implement. Performance of these filters was evaluated by computer simulations. It was found that both the optimum and the suboptimum filters performed significantly better than the nonadaptive filters and the optimum filters were slightly superior to the suboptimum filters.

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Estimating Year-to-Year Variability of Rainfall for Microwave Applications

H. T. DOUGHERTY AND E. J. DUTTON

Abstract—Recent progress is reported for extensions of the Rice-Holmberg rainfall-prediction model. This extension provides for the year-to-year variation expected for rainfall and is required to permit any useful comparison of predicted with observed rainfall (or predicted with observed microwave attenuation due to rainfall). The results are illustrated for Europe.

I. INTRODUCTION

In 1973, Rice and Holmberg [1] presented a worldwide rainfall prediction model. The model is designed specifically for telecommunication applications and consists of distributions of t-minute ($t = 1, 5, 30$, etc.) point-rainfall rates predicted from historical meteorological data. This prediction model contains three basic parameters: M, the annual rainfall in millimeters; β, the ratio of thunderstorm rain to total rain; and D, the annual number of days for which precipitation $\geqslant$0.25 mm. By relating D to the annual rainfall M and provid-

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